Spatial modelling of the variability of the soil moisture regime at the landscape scale in the southern Qilian Mountains, China

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Abstract

The spatial and temporal variability of the soil moisture status gives an important base for the assessment of ecological (for restoration) and economic (for agriculture) conditions at micro- and meso-scales. It is also an essential input into many hydrological processes models. However, there has been a lack of effective methods for its estimation in the study area. The aim of this study was to determine the relationship between the soil moisture status and precipitation and topographic factors. First, this study compared a linear regression model with interpolating models for estimating monthly mean precipitation and selected the linear regression model to simulate the temporal-spatial variability of precipitation in the southern Qilian Mountainous areas of the Heihe River Basin. Combining topographic index with the distribution of precipitation, we calculated the soil moisture regime in the Pailugou catchment, one representative comprehensive research catchment. The modeled results were tested by the observed soil water content for different times. The correlation coefficient between the modeled soil moisture status and the observed soil water content is quite high, assuring our confidence in the spatially-modeled results of the soil moisture status. The method was applied to the southern Qilian Mountainous regions. Therefore the modeled distribution of the soil moisture status reflected the interplay of the local topography and landscape climate processes. The driest sites occur on some ridges in northern part and western part of the study area, where have small accumulating flow areas and low precipitation rates. The wettest sites are registered in the low river valley of the Heihe River and its major tributaries in the eastern part due to large accumulating flow areas and higher precipitation rates. Temporally, the bigger variation of the soil moisture status in the study occurs in July and smaller difference appears in May.

Keywords: soil moisture status; precipitation; linear regression; topographic index; Qilian Mountains; Landscape scale

1 Introduction

The Heihe River Basin, the second largest inland river basin in the arid regions of northwestern China, consists of three major geomorphic units: the southern Qilian Mountains, the middle Hexi Corridor, and the northern Alxa Highland. The southern Qilian Mountains are hydrologically and ecologically the most important unit because of the functions as the water source to support the irrigating agriculture in the Hexi Corridor and also to maintain the ecological viability in the northern Alxa Highland. With the rapid growth of population, agricultural irrigation areas increasingly spread in the middle Hexi Corridor. As a result, the already-existing conflict between economic use of the water here and ecological demand of the water in the Alxa Highland has been recently exacerbated. How to resolve the conflict and coordinate the development in economy and ecological environments becomes the focus of attention in the Heihe River basin. Many researchers have dealt with water resources, such as water resources carry capacity (Ji, et al., 2006), ecological requirement water (Zhao, et al., 2005; Zhao et al., 2010), the runoff amount of the Heihe River and its variation (Wang, et al., 2009), methods of irrigation and so on. The water resources are very scarce in the Heihe River basin, and the runoff from the southern Qilian Mountains approximately represents the water resources amount of the middle Hexi Corridor and the northern Alxa Highland. Therefore, accurate estimation of runoff from Qilian Mountainous watersheds is an urgent need for answering Heihe River water resources carry capacity and for water management and planning. To accomplish the needed runoff estimation in the upper reaches, several distributed hydrological models are applied for the practical purpose. Soil moisture is considered to be an important parameter in these distributed hydrology models. It thus has to be spatially and temporally portrayed (Liang et., 1994; Wignosta et al., 1994; Famiglietti and Wood, 1994; Li & Islam, 1999). For the reason, during the last 30 years there have been various studies that have attempted to develop a method to estimate the soil moisture content over large scale. The one commonly used is extrapolation approach in which one method is to estimate soil moisture by extrapolating point measurements across the landscape with geostatistical techniques (Western and Grayson, 1998;

Wang et al., 2001;Western et al., 2004). Unfortunately, ground-based methods (e.g. neutron thermalization, oven-dry method) are much too labor-intensive to maintain for a large area (e.g., in the entire southern Qilian Mountains). Another method is to estimate soil moisture by using wetness indices based on terrain information (e.g. Beven and Kirkby, 1979; O'Loughlin, 1986; Svetlitchnyi et al., 2003; Teuling and Troch, 2005). The latter method hypothesizes that the spatial distribution of topographic attributes that characterize these flow paths inherently captures the spatial variability of soil moisture status at the meso-scale as well. However, soil moisture patterns are influenced by a number of factors such as soil properties, vegetation, depth to water table and meteorological conditions besides topographic attributes. Climate, parent material, topography, vegetation, and other biotic agents are the dominant soil-forming process, but climate probably exert control at larger scales (Moore et al., 1988; Gómez-Plaza et al., 2001). Thus, in this study the relationship of the temporal and spatial variation of soil moisture is determined by establishing its controlling factors, e.g. topography and precipitation. Topographic attributes can be easily extracted from a digital elevation model (DEM). Whereas, precipitation fields on a regular grid and in digital forms must be inferred from neighbouring meteorological stations or from relationships with other variables (Marquínez et al., 2003). There are many methods of interpolating precipitation from monitoring stations to grid points (Dirks et al., 1998; Goovaerts, 2000; Wei, et al., 2005; Price et al., 2000; Guenni & Hutchinson, 1998). Basic techniques use only the geographic coordinates of the sampling points and the value of the measured variable. However, the study area is one in which these methods have not been applied previously. In addition, regression models are using only additional information as regression models between precipitation and various topographic variables such as altitude, latitude, continentality, slope, orientation or exposure (Basist et al., 1994; Goodale et al., 1998; Ninyerola et al., 2000; Wotling et al., 2000; Weisse & Bois, 2001). But few researchers could interpolate precipitation by regression models in the study area because of unavailable digital elevation models (DEM). Fortunately, significant progress in this area has recently been achieved through the development of a high-resolution DEM with a resolution of 10m×10m by the remote sensing laboratory of Cold and Arid Regions Environmental and Engineering Research Institute, CAS. The topographic factors of soil moisture are best delineated by the DEM at the resolution that closely matches the smallest orographic scale supported by the data.

This study sought to develop the relationships between soil moisture and its controlling factors (i.e., precipitation and topographic variables) in order to map the soil moisture status across the southern Qilian Mountains. In the following sections we will present the various steps that lead to the mapping of the soil moisture regime: (1) use of available data; (2) determination of the best model for modelling the areal distribution of precipitation; (3) definition of the wetness index and GIS realization of the wetness index model; (4) mapping of the soil moisture status distribution; and finally (5) validation of the results.

2 Materials and methods

2.1 Study area

The study area, one portion of the Qilian Mountains within the Heihe River Basin, is located between $98^{\circ}34'$ - $101^{\circ}11'$ E and $37^{\circ}41'$ - $39^{\circ}05'$ N and covers an area of approximately 10, 009 km^2, with the elevation ranging from 2000 to 5500m a.s.l. Administratively, the major part of the study area is in Gansu Province and a small part in Qinghai Province (Fig. 1). The mean annual precipitation increases with the increasing elevation (from 250 to 700mm). The inter-annual variability in the precipitation is as high as 80%, and over 88% of the precipitation falls between May and September. Figure 2 shows the pattern of rainfall over the year in Zhamashike meteorological station (one representative meteorological station in the study area). The mean annual temperature decreases with the increasing elevation (from 6.2 to -9.6°C). The vegetation distribution closely follows the temperature- and precipitation-determined heat-water combinations in the Mountains. They are (from low to high elevations): desert steppe, forest steppe, sub-alpine shrubby meadow, alpine cold desert, and ice/snow zone. In addition to the obvious vertical zonality, horizontal zonality also exits due to precipitation and air temperature differences from the south to the north and from the east to the west. Generally, precipitation decreases from the east to the west and increases from the north to the south but the temperature is reverse in the study area.

Figure 1 Location of the study area, meteorological stations and rain gauges.

Figure 2 Distribution of monthly mean precipitation in Zhamashike meteorological station (1957-1995).

2.2 Data collection

The monthly mean precipitation data (from 1957 to 1995) were obtained from 43 stations, including meteorological stations and rain gauges located within the study area and the surrounding areas. The locations and the altitudes of these stations were measured with a global positioning system (GPS) and an elevation meter. Among them, 30 stations were chosen to develop the regression model or to use for interpolating and other 13 stations were remained to test the models. Total 27 plots were located to measure soil water content, 22 plots were in Pailugou catchment (one representative comprehensive research catchment in the study area located at 38.55^{o} N, 100.30^{o} E) (Fig. 1). Pailugou catchment covers an area of 10 km^2, with the elevation ranging from 2600m to 3800m a.s.l. Soil was sampled on a biweekly interval at four depths (0-10, 10-20, 20-40, 40-60 cm) from May to September in 2003 and 2004. Soil moisture was measured by the conventional oven-dry method. Calculation of mean value of soil water content (SWC) is demonstrated as follows: suppose that SWC of plot i, layer j, sampling occasion k is expressed as $SWC_{i,j,k}$. N_j represents the number of sampling soil layer or soil depths and is 4 in this study; N_k is the number of sampling occasion in each month, which is 2. Mean SWC in each month on plot i (SWC_i) is calculated as follows:

$$SWC_i = \frac{1}{N_k \times N_j} \sum_{k=1}^{2} \sum_{j=1}^{4} SWC_{i,j,k} \qquad (1)$$

At final, we can get available data of 15 plots, which was used to validate the model mentioned hereinafter. Pailugou catchment has a weather station at the catchment outlet. 16 rain gauges were located along elevation gradient, on a 100m interval between 2600-3500m and on a 50m intervals between 3500-3800m, for providing information on the spatial variability of rainfall.

DEMs of the study area and Pailugou catchment were obtained from the remote sensing laboratory of Cold and Arid Regions Environmental and Engineering Research Institute, CAS.

2.3 Description of models

Hydrological prediction at the micro- and meso-scales is intimately dependent on the ability to characterize the spatial variability of the soil water content. However, soil moisture exhibits drastic temporal and spatial variations even in a small catchment. In mountainous terrains, the soil water distribution is controlled by vertical and horizontal water divergence and convergence, infiltration recharge, and evapotranspiration. The latter two terms are affected by solar insolation and the vegetation canopy that vary strongly with exposure in arid areas. The divergence/convergence term is dependent on hill-slope position (Moore et al., 1993). Considering the hill-slope position, most index approaches for predicting the spatial distribution of soil water can be expressed as (Beven and Kirkby, 1979):

$$IN_1 = ln\ (a/tan\beta) \quad (2)$$

where IN_1 is the wetness index, α the contributing area and β the local slope of the terrain. The soil water content is not only affected by the divergence/convergence of water but also affected by evapotranspiration. In arid areas, evapotranspiration is obviously different in different aspects because of variations of insolation. A modified wetness index is defined by merely introducing the factor of aspect (A), an appropriate surrogate of potential insolation (Grayson et al., 1997; Gomez-Plaza et al., 2001). Then, the Eq.(2) becomes:

$$IN_2 = ln\ (a/tan\ \beta) \times cosA \qquad (3)$$

where IN_2 is the modified wetness index and A the aspect.

The soil moisture index at landscape scales is determined by high-resolution spatial distributions of precipitation and DEM-based topographic factors (Dymond and Johnson, 2002) and given as the following:

$$IN_3 = ln(a/tanB) \times cosA \times P_i \qquad (4)$$

where IN_3 is the soil moisture index in every month, P_i the monthly mean precipitation. Eq.(4) requires four parameters: slope, aspect, the specific catchment area (catchment area draining across a unit width of contour) and precipitation. Topographical parameters such as slope (β), aspect (A), and the contributing area (α) are computed from DEM. Precipitation is an important parameter and must be accurately estimated.

The temporal and spatial distribution of precipitation in Pailugou catchment was simulated by regression relationship between the monthly mean rainfall and altitude, which is presented as:

$$P_i = a + bH + cH^2 \qquad (5)$$

where H is the altitude in meter, a, b and c the regression coefficients (Table 1)

We here used five methods to simulate the temporal and spatial distribution of precipitation in the southern Qilian Mountains, i.e. linear regression, inverse distance weighted (IDW), ordinary kriging (OK), trend and spline. The regression model derived by regression analyses can predict annual, monthly precipitation as functions of elevation and geographical coordinates (Wei et al., 2005; Michaud et al., 1995). By the analysis of the precipitation data with their elevation and geographical coordinates in the study, a linear regression relationship between the monthly mean rainfall and locational/topographic factors is presented as:

$$P_i = a + bH + cY + dX \tag{6}$$

where H is the altitude in meter, Y the latitude in degree, X the longitude in degree and a, b, c, d the regression coefficients (Table 2).

Table 1

Table 2

Besides the regression model, four conventional interpolation methods, inverse distance weighted (IDW), spline, ordinary kriging (OK), and trend, were tested. IDW estimates the value of an unsampled area as a weighted average of a defined number of neighborhood points, or area, and the weight assigned to each neighborhood point diminishes as the distance to the neighborhood point increases (Lloyd, 2005). Spline interpolators have been widely used in developing climatic surfaces from sparse observation points (Tsanis and Gad, 2001). The interpolated surface based on spline

(a) passes exactly through the data points and (b) has a minimum curvature. OK is a geostatistical procedure that uses a variogram model, which describes the spatial continuity of the input data to estimate values at unsampled locations (Isaaks and Srivastava, 1989). The variability between samples as a function of distance (i.e., semivariance) is evaluated and modeled prior to kriging (Wackernagel, 1995). The trend surface interpolator uses a polynomial regression to fit a least-squares surface to the input points. It creates smooth surfaces. The surface generated will seldom pass through the original data points since it performs the best fit for the entire surface.

3 Results and discussion

3.1 Wetness indexes

Topographical parameters, such as slope, aspect and the contributing area were computed from DEM. The aspect is expressed in positive degrees from 0 to 360, measured clockwise from the north. The maps of the wetness index (IN_1 and IN_2) and the modified wetness index (IN_3) in Pailugou catchment were obtained from the models using ARC/INFO + grid. The simulated wetness indexes were validated by observed data. We found that IN_1 was able to explain between 34% and 38% of the spatial variability of soil moisture, but if the aspect was considered as a complementary factor, this capacity increased up to 69.5%. The results were supported by some researches (Moor et al., 1988; Gómez-Plaza et al., 2001). However, Eq. (2) and Eq. (3) only take the topographic factors into account. If the spatially inhomogeneous precipitation was considered as another complementary factor (i.e. Eq. (4)), the capacity of the spatial variability of soil moisture can be explained to be 76%

in Pailugou catchment (Fig. 3). The maps of the wetness index (IN_1) and the modified wetness index (IN_2) in the southern Qilian Mountains were obtained from the models using ARC/INFO + grid (Fig. 4). According to precipitation measurement, precipitation shows dramatically differences in the southern Qilian Mountains. It increases from the north to the south, from the lower altitude to the higher altitude, and decreases from the east to the west. In turn, the soil moisture status exhibits a spatially inhomogeneous arrangement in the landscape due to precipitation. Therefore, precipitation must be considered.

Figure 3 Scatter plots of observed soil moisture content and modeled soil moisture status from May to August

Figure 4 Distribution of wetness indexes (IN_1 and IN_2) in the southern Qilian Mountains.

3.2 Spatial and temporal distributions of precipitation

Prediction of precipitation on the locations of the validation points and the measured values at these locations were compared by three criteria: the mean error (ME), the mean absolute error (MAE) and the root mean square error (RMSE). ME indicates the degree of bias, MAE provides a measure of how far the estimate can be in error, ignoring the sign, and RMSE provides a measure that is sensitive to outliers. A summary of the errors obtained from the criteria was presented in Table 3. ME was relatively low for IDW, OK, trend and linear regression, but was generally lowest for the linear regression model. The linear regression and OK methods gave the lower MAE and RMSE. The spline gave consistently poor performances. For five methods, there were substantial variations in RMSE through the year (Fig. 5). The highest errors occurred from July to September and the lowest values from October to February, which probably reflected the greater precipitation differences across the region in summer. From June to August, the linear regression performed better than OK. Thus the conclusions are as follows: on average over the year, larger predictions errors were obtained by the spline, the trend and IDW methods that ignore elevation factors, with the worst results produced by the spline. It was noteworthy that for several months (from January to May, from September to December), OK yielded smaller prediction errors than the linear regression of precipitation against elevation and locational/topographic factors.

Table 3

Figure 5 Validation RMSE for monthly mean precipitation averaged across 13 test stations for five methods.

As mentioned above, over 88% of the precipitation falls between May and September and over 63% between June and August in the southern Qilian Mountainous areas of the Heihe River Basin. We were here focusing on the spatial distribution of precipitation during the ecologically meaningful time period, i.e., growing seasons approximately from May to August. Our comparison between these models' performances demonstrated that the linear regression model did the best job during the ecologically meaningful time period. The best performance of the linear regression in the study area made this model the best choice. A series of spatial-distribution maps of precipitation were obtained by the regression model (Fig.

6). Figure 6 showed that lower precipitation values were registered in the low valleys of the Heihe River and the northwest part, and higher precipitation values appeared in the southeast part where the altitude and longitude depended precipitation is higher. Figure 6 also showed that precipitation value had temporal variations during growing seasons (i.e. from May to August), highest precipitation value, ranging from 46mm to 145.4mm, appearing in the July, and the lowest precipitation value, from 25.2mm to 64.5 mm, being seen in May.

Figure 6 Distribution of monthly mean precipitation in southern Qilian Mountains from May to August.

3.3 Temporal and spatial distribution of soil moisture status in the southern Qilian Mountains.

The soil moisture data are fairly sparse in the study area. We could not collect the soil moisture data except in Pailugou catchment. The soil moisture status of Pailugou catchment was simulated using Eq.(4). To test the spatially-modeled results of the soil moisture status in the catchment, we compared the observed results for 4 months at 15 sample plots with the spatially-modeled results for the corresponding months and sample plots. The correlation coefficients (R^2) are from 0.60, 0.76, 0.67, 0.69 for May, June, July and August respectively (Fig. 3). These assure our confidence in the spatial model (i.e. Eq.(4)) of the soil moisture status.

Therefore, the same strategies were employed to estimate the soil moisture status of the southern Qilian Mountains areas (Fig. 7). The distributions of the soil moisture status in the study area reflected the interplay of the local and landscape climate processes. As viewed from a small scale, the gentle bases of long hill-slopes had more moisture than the steep short sites due to its larger catchment areas, and the south-facing slope had less moisture than the north-facing slope because it got more insolation on the dryness of the matrix soil water. From the landscape scale viewpoint, the moisture increased from the north to the south and from the west to the east due to the precipitation increase. Figure 7 showed that the driest sites (IN_3 from –1412 to –985) occurred on some ridges in the northern part and the western part of the study area, which has very small catchment areas and small precipitation. The wettest sites (IN_3 from 1150 to 1577) were registered in the low valleys of the Heihe River and its major tributaries in the eastern part due to large accumulating flow areas and more precipitation. The bigger variation of the soil moisture status in the study occurred in July and smaller difference appeared in May. Although there is temporal different in the status of soil moisture, the spatial variation trend of soil moisture in different month is the same. Comparing the dominant communities at 35 sample points extracted from the present distribution of vegetation types with the spatially-modeled results of soil moisture in June for the corresponding sample points (Table 4), we found a certain community occupies its special range of soil moisture. For example, Qinghai spruce (*Picea crassifolia*), distributing north-facing slope in the Qilian Mountains, dominates the range of soil moisture (NI_3) between 0-800. *Stipa breviflora*-*Stipa bungeana* has a range of soil moisture between -100-600 with higher frequency between -100-200. *Stipa przewalskyi*-*Stipa purpurea* community covers a range of soil moisture between -100-700 with higher frequency between 200-600.

Salix gilasnanica dominates a range between 300-1200, distributing above the upper line of Qinghai spruce forest on the north-facing slope. *Kobresia tibetica* is dominant species of the alpine meadow in Qilian Mountains. which occupies higher range of soil moisture between 500-1400 with higher frequency between 800-1100.

Figure 7 Distribution of monthly mean soil moisture status in southern Qilian Mountains from May to August.

Table 4 A range of soil moisture (NI_3) in five plant communities in southern Qilian Mountains

In addition to topography, the land use type is another important factor controlling soil water patterns, which means that difference in vegetations resulting from different land use types was one of the major factors influencing soil moisture variability. However, the factor of vegetations is not included in Eq. (4). How to improve the model to estimate the soil moisture status is an objective of our future study.

4 Conclusions

Accurate prediction of the soil moisture status at the large scale is of crucial interest to hydrology and agronomy related studies in the southern Qilian Mountains. However, soil moisture data are not available and ground-based methods (e.g. neutron thermalization, oven-dry method) are far too labor-intensive to maintain for the large area (e.g., the entire southern Qilian Mountains). Therefore, it is very important to develop more descriptive models of the soil moisture status. We can draw some conclusions from the approach:

1. Equation (4) was used to predict the variability of the soil moisture status in the study area and the model was validated by Pailugou catchment. The results of validation assured our confidence in the spatially-modeled results of the soil moisture status. But one important factor affecting soil moisture is vegetation types which were excluded in the model. Vegetation, which is in part responsible for the distribution of soil moisture, will be integrated in equation (4) to improve the estimation accuracy in future work. Further studies would benefit from using these types of index to set up the distributed initial soil water conditions in the hydrological modeling of the study area incorporating estimated evapotranspiration fluxes of vegetation.

2. Equation (4) includes two terms, the topographic indices and precipitation. The model of the topographic indices in Eq. (3) is universal in a different sense. Therefore accurate estimations of precipitation are very important to estimate the soil moisture state at large scale. We selected five methods to simulate the temporal-spatial distributions of precipitation in the study. By comparison, the best performance of the linear regression in the study area made this model the best choice.

3. Soil moisture status is influenced by other factors, such as soil properties, vegetation, meteorological conditions besides topography. The importance of these factors can vary with the study area. Any simple relationship between topographic indices and soil moisture must, however, be used with great care (Rodhe and Seibert, 1999; Svetlitchnyi et al., 2003). According to Florinsky et al. (2002) in soil studies with digital terrain modelling, there is a need to take into account four types of

variability in relations between soil and a relief: regional, time, depth, and scale. For example, Chinese Loess Plateau comparing with the southern Qilian Mountains, three natural factors: steeply-sloped topography with gullies, fine-textured loessial soils and precipitation in form of storms are first and foremost considered. These factors decide the unique hydrogeomorphic condition that the rainfall intensity often exceeds the soil infiltration capacity differing from that in the southern Qilian Mountains. This imposes on equation (4) quite certain regional restrictions.

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Table 1. Monthly regression coefficients and R^2 needed to calculate monthly mean precipitation using altitude (*H*) for Pailugou catchment ($P = a + bH+cH^2$).

time	*a*	*b*	*c*	R^2
Apr.	**-0.00002**	**0.1344**	**-194.41**	**0.965**
May	**-0.00004**	**0.2386**	**-345.24**	**0.969**
Jun.	**-0.00020**	**0.9756**	**--1411.6**	**0.968**
Jul.	**-0.00010**	**0.7745**	**-1120.7**	**0.968**
Aug.	**-0.00005**	**0.3489**	**-504.77**	**0.967**
Sep.	**-0.00006**	**0.3770**	**-545.41**	**0.967**

Table 2. Monthly linear regression coefficients and R^2 needed to calculate monthly mean precipitation using altitude (*H*), latitude (*Y*) and longitude (*X*) for the southern Qilian Mountains ($P = a + bH + cY + dX$).

time	*a*	*b*	*c*	*d*	R^2
Jan.	**-19.811**	**0.000260**	**-0.051**	**0.231**	**0.207**
Feb.	**-70.701**	**0.001103**	**0.221**	**0.626**	**0.331**
Mar.	**-249.545**	**0.003390**	**0.433**	**2.336**	**0.406**
Apr.	**-16.862**	**0.004009**	**-4.289**	**1.879**	**0.584**
May	**408.331**	**0.009569**	**-12.540**	**0.869**	**0.810**
Jun.	**530.716**	**0.021000**	**-13.656**	**0.016**	**0.863**
Jul.	**689.699**	**0.029650**	**-12.485**	**1.018**	**0.870**
Aug.	**495.902**	**0.018520**	**-19.839**	**2.869**	**0.879**
Sep.	**196.940**	**0.009100**	**-15.049**	**4.003**	**0.856**
Oct.	**-5.170**	**0.002153**	**-5.737**	**2.341**	**0.841**
Nov.	**-136.015**	**0.000984**	**0.240**	**1.283**	**0.455**
Dec.	**-81.180**	**0.000480**	**0.493**	**0.627**	**0.166**
Annual	**1742.001**	**0.097260**	**-87.915**	**17.197**	**0.861**

Table 3. Validation errors averaged across 13 test sites for the five interpolation methods in each month.

	Models	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
ME	IDW	0.20	0.95	2.56	0.83	-1.2	5.97	-2.58	1.28	-4.56	0.3	-0.68	0.59
	TREND	0.31	0.72	1.32	5.33	0.40	0.64	0.31	0.72	1.32	5.33	0.40	0.64
	OK	0.22	0.97	2.54	1.48	0.35	6.73	-2.23	2.66	-3.78	0.75	-0.65	0.58
	SPLINE	0.42	1.16	3.65	2.59	1.27	9.98	-0.94	4.5	-3.3	1.02	-0.38	0.7
	REGRESSION	0.32	1.04	2.3	0.36	-1.51	6.15	-3.56	-0.23	-6.09	-0.57	-0.75	0.7
MAE	IDW	0.84	1.56	4.46	5.34	6.84	11.41	12.68	9.98	6.47	3.1	1.52	1.15
	TREND	1.06	2.09	5.24	6.10	6.34	11.89	10.93	8.44	7.53	3.17	1.67	1.33
	OK	0.84	1.89	5	4.85	4.57	8.15	8.18	7.06	4.8	1.63	1.41	1.18
	SPLINE	0.97	1.81	7.29	6.99	7.04	12.18	12.57	9.71	6.68	2.79	1.51	1.47
	REGRESSION	1.05	1.98	4.94	5.86	5.03	7.46	6.07	4.6	7.41	2.92	1.72	1.3
RMSE	IDW	1.19	1.94	5.65	6.53	8.56	13.50	15.47	12.72	8.23	3.51	1.71	1.35
	TREND	1.28	2.22	8.13	8.88	8.52	15.01	15.80	10.52	8.23	3.88	1.88	1.79
	OK	1.18	2.16	6.16	6.21	5.54	10.78	9.75	8.62	6.05	2.18	1.65	1.37
	SPLINE	2.22	8.13	8.88	8.52	15.01	15.80	10.52	8.23	3.88	1.88	1.79	2.22
	REGRESSION	1.27	2.32	6.16	6.63	6.10	9.47	8.33	7.39	9.21	3.51	2.08	1.53

Table 4 A range of soil moisture (NI_3) in five plant communities in southern Qilian Mountains

NI_3 classes	Frequency of five communities				
	Stipa breviflora - Stipa bungeana	*Stipa przewalskyi - Stipa purpurea*	*Picea crassifolia*	*Salix gilasnanica*	*Kobresia tibetica*
-100-0	14.29	2.70	0.00	0.00	0.00
0-100	20.00	5.41	2.94	0.00	0.00
100-200	25.71	2.70	2.94	0.00	0.00
200-300	34.29	18.92	11.76	0.00	0.00
300-400	0.00	18.92	17.65	5.71	0.00
400-500	0.00	29.73	23.53	5.71	0.00
500-600	5.71	18.92	23.53	8.57	3.23
600-700	0.00	2.70	11.76	5.71	9.68
700-800	0.00	0.00	5.88	8.57	6.45
800-900	0.00	0.00	0.00	25.71	19.35
900-1000	0.00	0.00	0.00	25.71	19.35
1000-1100	0.00	0.00	0.00	5.71	22.58
1100-1200	0.00	0.00	0.00	8.57	9.68
1200-1300	0.00	0.00	0.00	0.00	6.45
1300-1400	0.00	0.00	0.00	0.00	3.23

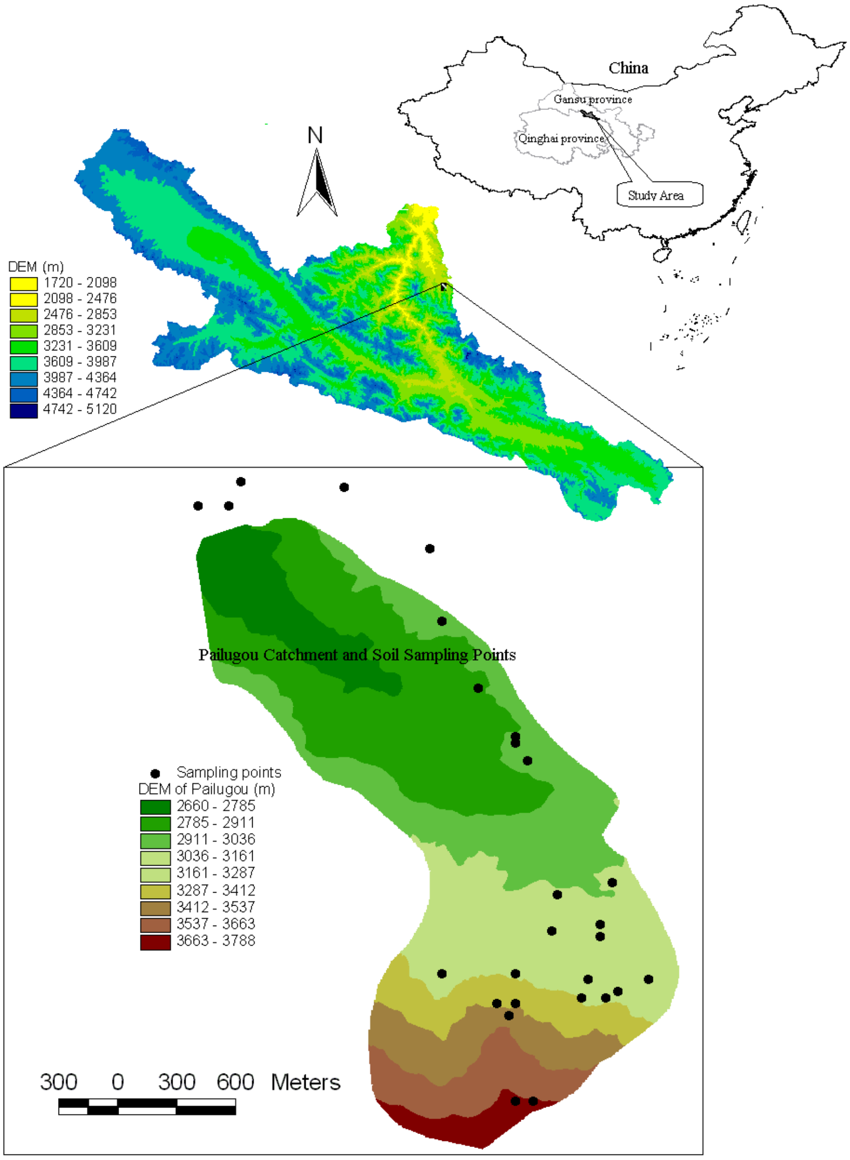


Figure 1. Location of the study area, meteorological stations and rain gauges in Pailugou catchment.

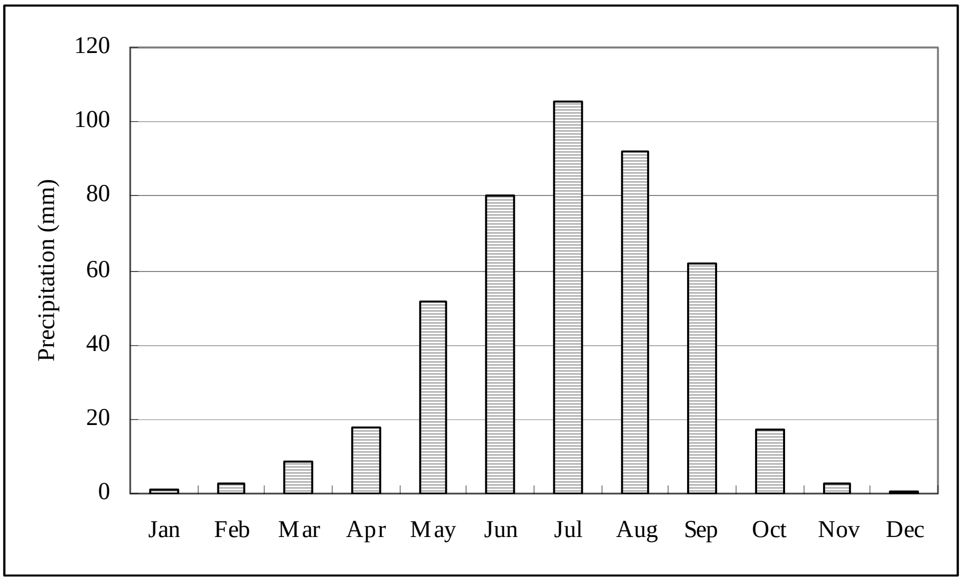
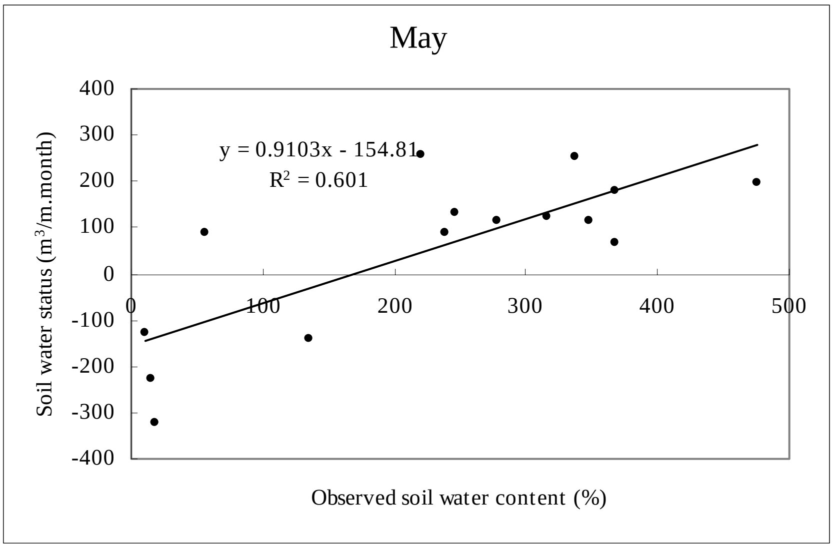
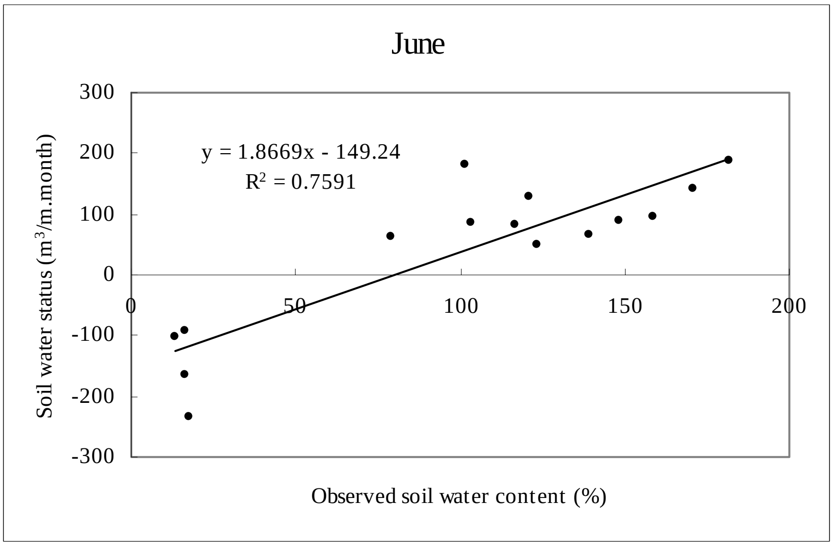
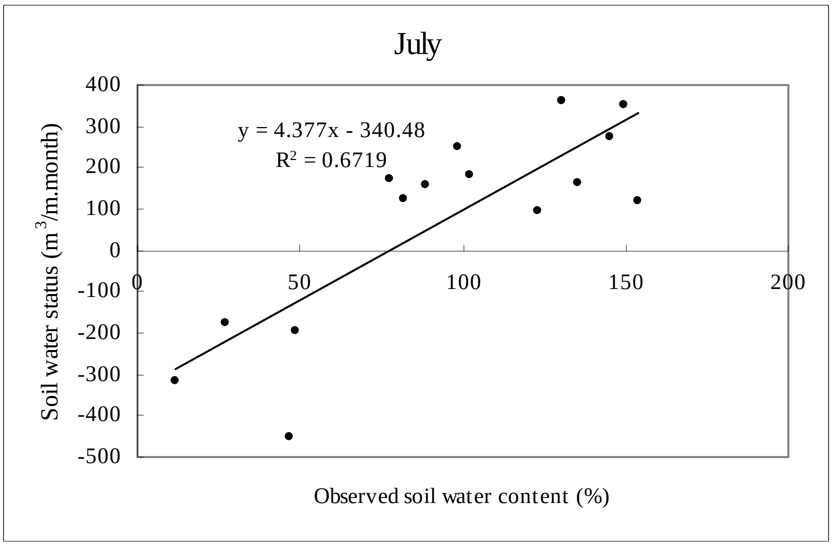


Figure 2. Distribution of monthly mean precipitation in Zhamashike meteorological station (1957-1995).


May
y = 0.9103x - 154.81
R2 = 0.601
Soil water status (m3/m.month)
Observed soil water content (%)
400
300
200
100
0
-100
-200
-300
-400
0
100
200
300
400
500


June
y = 1.8669x - 149.24
R2 = 0.7591
Soil water status (m3/m.month)
Observed soil water content (%)
300
200
100
0
-100
-200
-300
0
50
100
150
200


July
y = 4.377x - 340.48
R2 = 0.6719
Soil water status (m3/m.month)
Observed soil water content (%)
400
300
200
100
0
-100
-200
-300
-400
-500
0
50
100
150
200

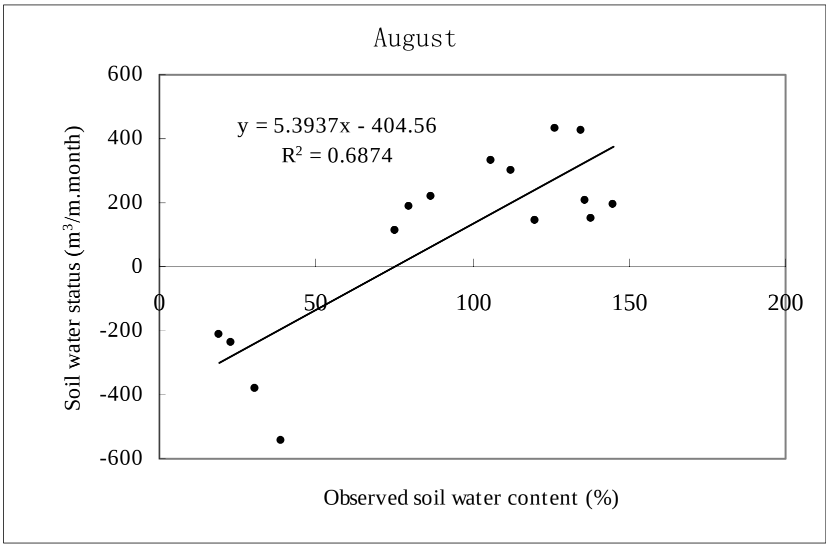


Figure 3. Scatter plots of observed soil moisture content and modeled soil moisture status from May to August

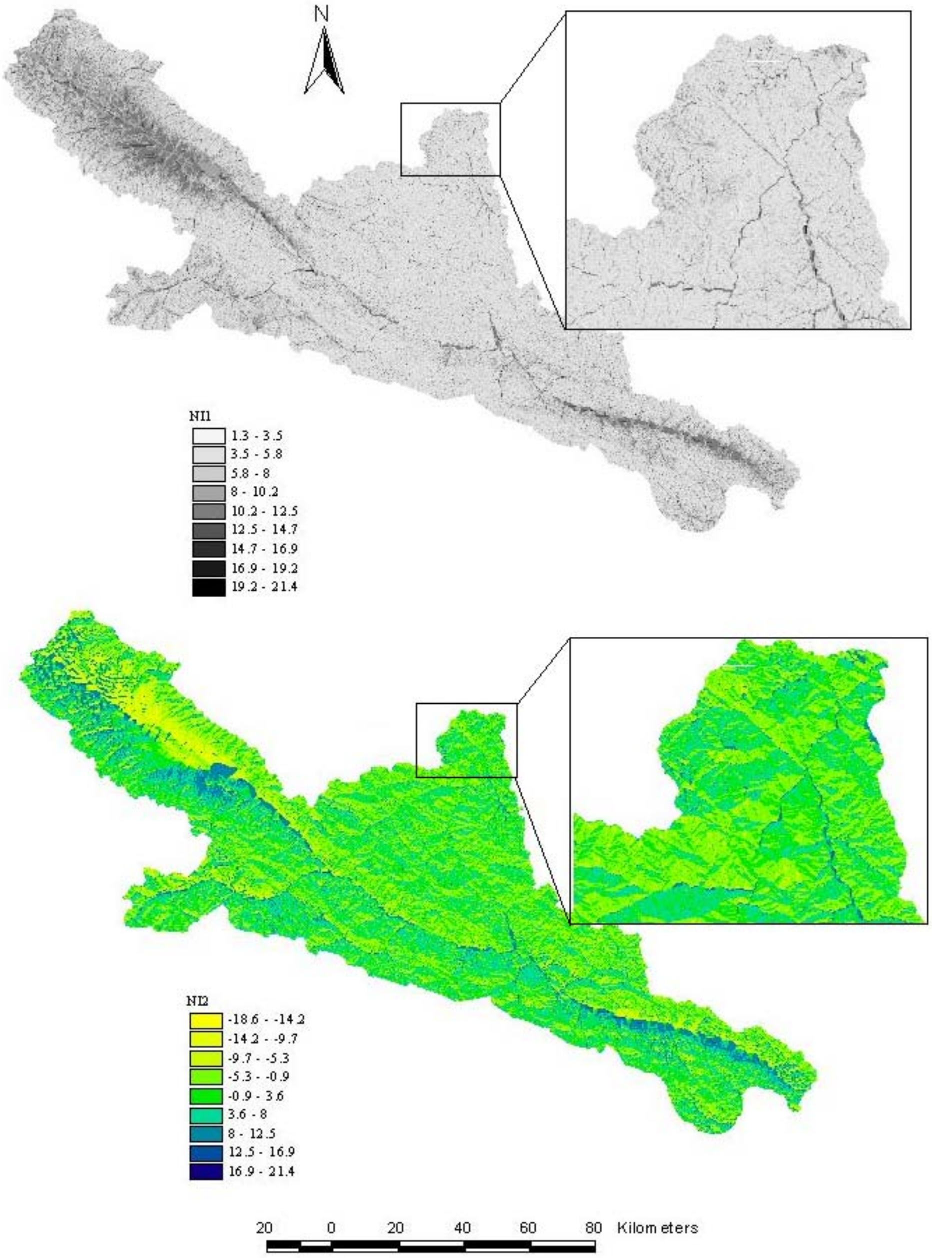


Figure 4. Distribution of wetness indexes (IN_1 and IN_2) in the southern Qilian Mountains.

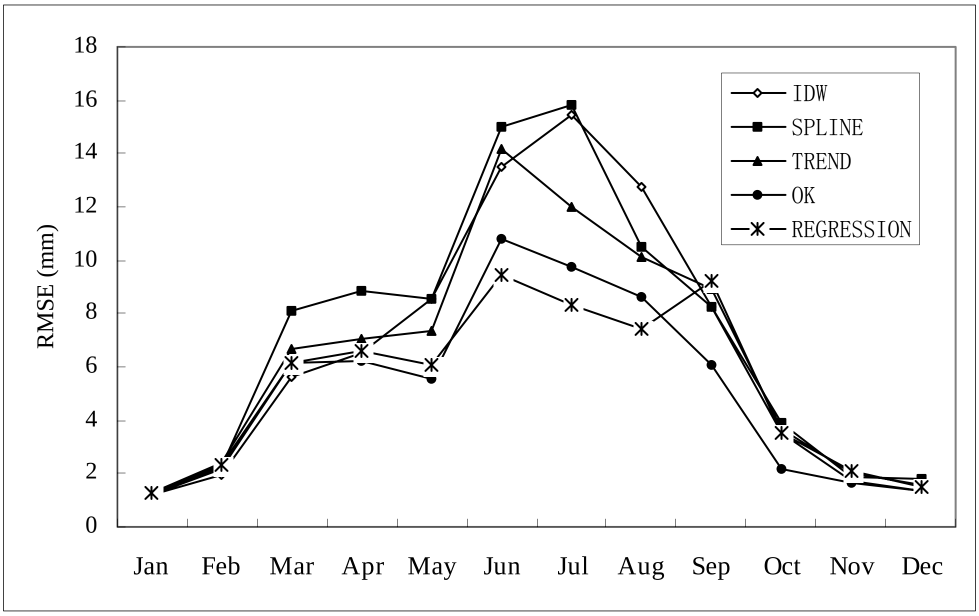


Figure 5. Validation RMSE for monthly mean precipitation averaged across 13 test stations for five methods.

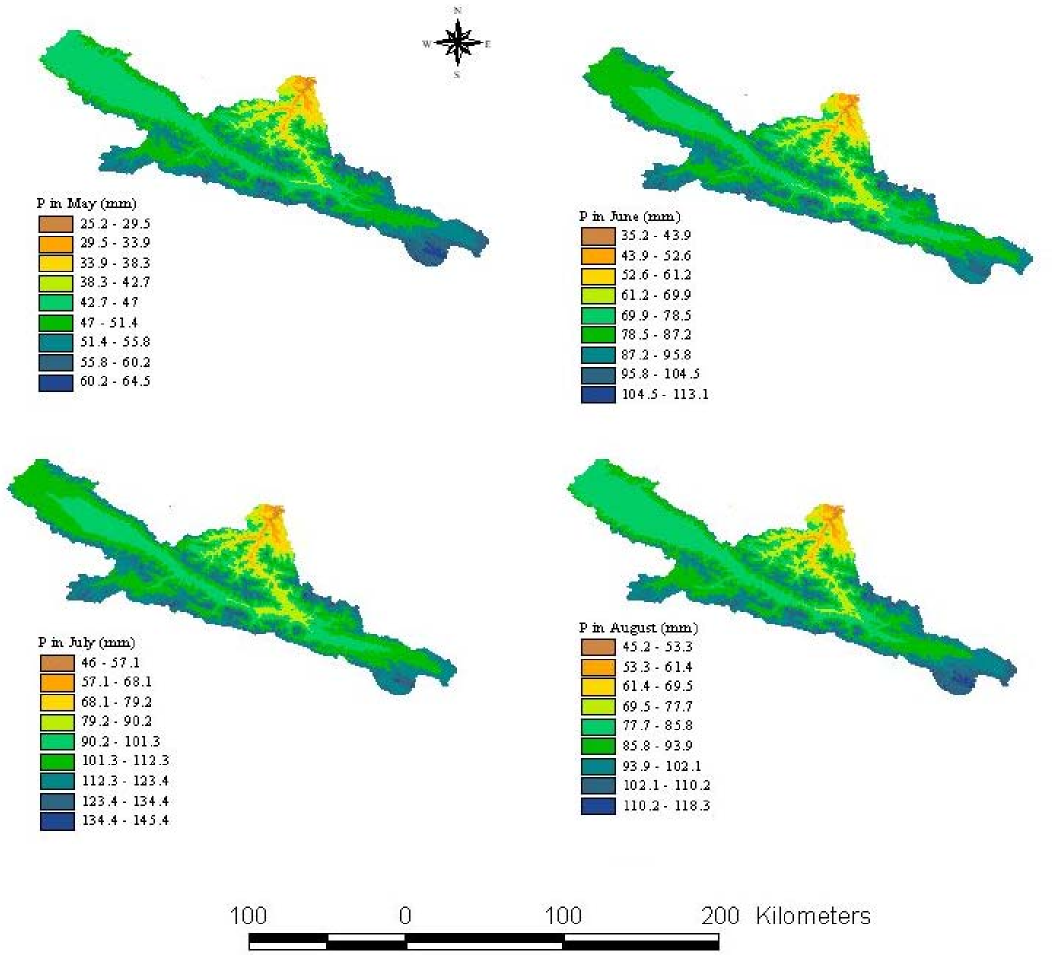


Figure 6 Distribution of monthly mean precipitation in southern Qilian Mountains from May to August.

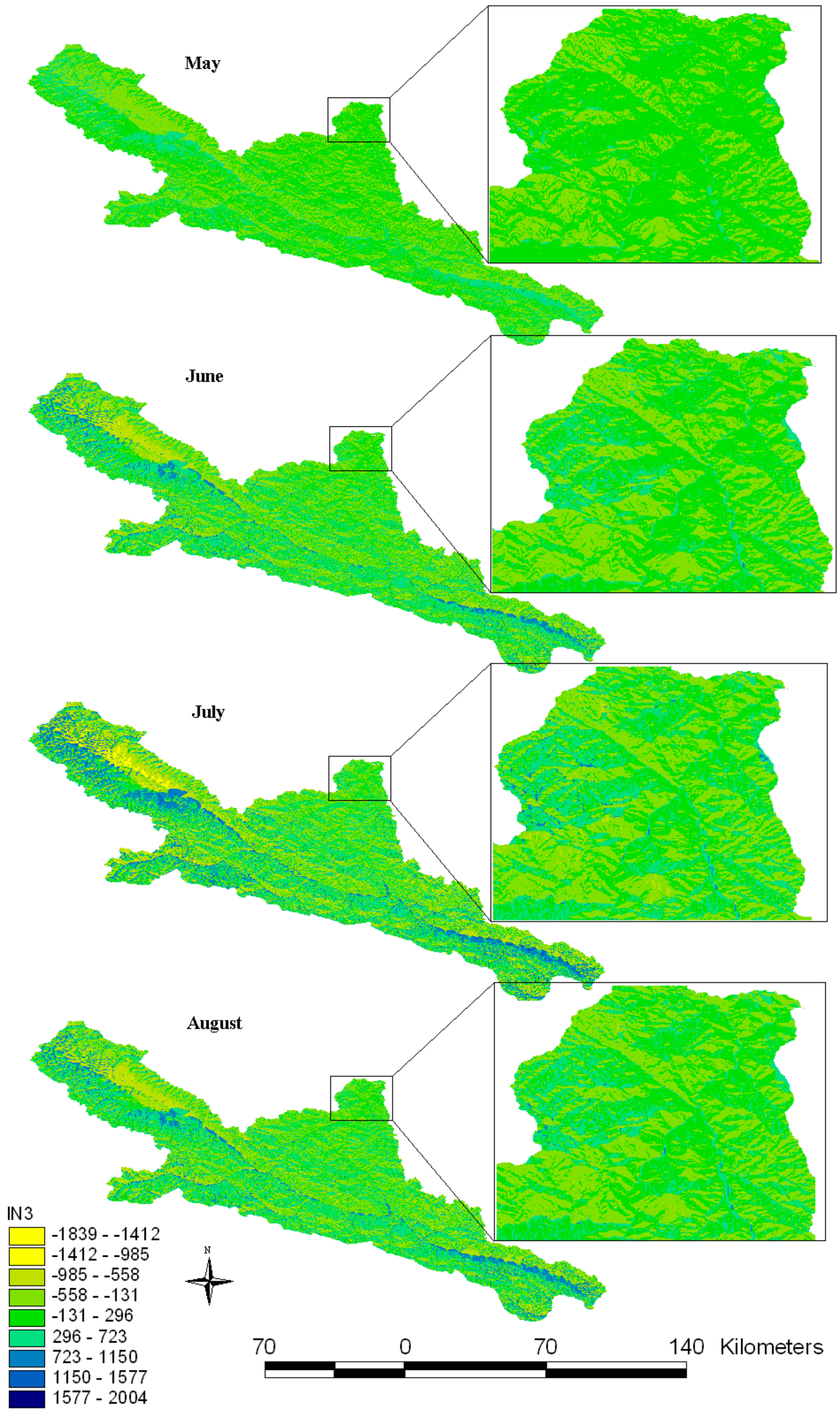


Figure 7. Distribution of monthly mean soil moisture status in southern Qilian Mountains from May to August.